Online Appendix

The Demand for Counterfeits: A Descriptive Analysis

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A Literature Summary

Table A.1 summarizes research on counterfeit demand and two adjacent literatures—demand for luxury/status goods and digital piracy. To our knowledge, empirical studies of counterfeit demand rely primarily on experiments and surveys, which measure stated rather than revealed behavior.[1] Field-based studies related to counterfeits exist but typically do not observe actual counterfeit consumption.

Han, Nunes, and Drèze (2010) assemble enforcement records and website listings (Thailand IP authority; knockoffbag.com) to study brand prominence and which luxury styles are *copied*. The evidence is illustrative (about 500 items) but not large-scale demand data, nor does it track purchases. Our study instead uses large-scale transaction data—millions of orders—to examine realized counterfeit purchasing and its socioeconomic correlates at the ZIP-code levels.

A separate line of work by Qian and coauthors uses firm-side panels to study how *authentic* producers respond to counterfeit entry and the substitution/advertising effects on *genuine* sales (Qian 2008; Qian, Gong, and Chen 2015; Qian 2014). Recognizing the scarcity of revealed-preference demand data, Qian and Xie (2014) develop a nonparametric data-fusion approach to study motivations, but counterfeit consumption in that analysis remains survey-based.

B Additional Information on the Empirical Context

Supply side. The platform mitigates legal risk in two ways. First, it suppresses brand names in search. A query for the correct spelling "louisvuitton bag" returns no results (Figure A.1a), yet a misspelling such as "louisvuittonn bag" yields 279,769 listings (Figure A.1b). Guides on the platform's subreddit teach buyers to use code-words—for example, "monogram tote" for a Louis Vuitton Neverfull or "flying jumpman" for Air Jordan sneakers—to evade the filter.

Second, sellers may not state that items are counterfeit. They hint at it with euphemisms ("luxury designer," "1:1 replica," "original quality") and blurred logos. The listing in Figure A.2

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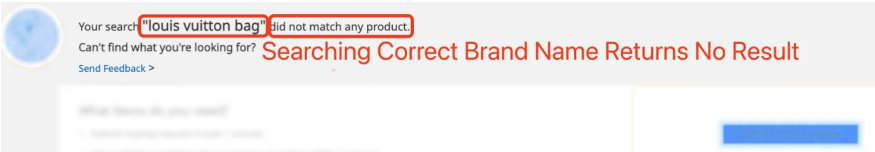
[1]Surveys likewise dominate industry reports (e.g., Alhabash et al. 2023; Civic Science 2019; INTA 2019; World Intellectual Property Organization (WIPO) 2010).

Table A.1: Summary of Related Literature

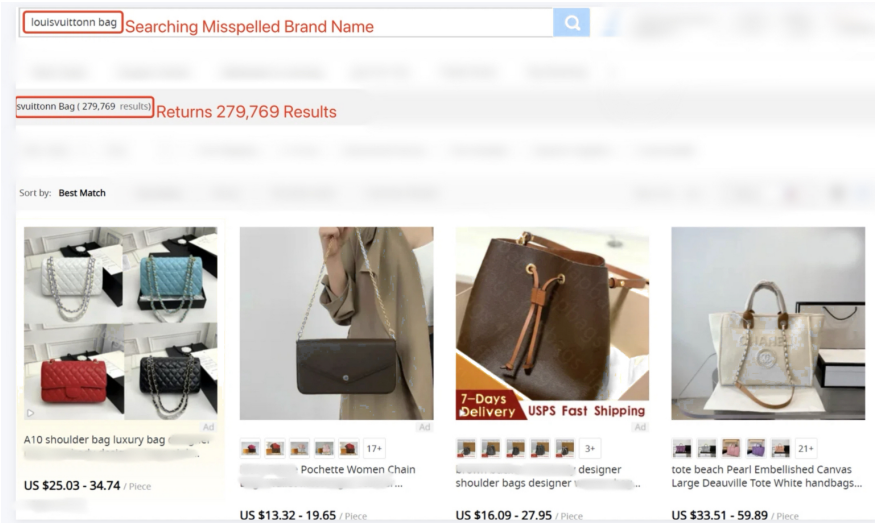
Question	Method/Data	Key Ideas	Literature
A. Counterfeit Demand			
Who/Why Buy?	**Field Data**	**Document relationship between income and counterfeit consumption.**	**This Paper.**
	Field Data & Survey	Preference for authentic versus counterfeit luxury goods.	Han, Nunes, and Drèze (2010) and Qian and Xie (2014)
	Survey	Consumers' incentives for intentionally purchasing counterfeit.	Wee, Ta, and Cheok (1995), Albers-Miller (1999), Tom et al. (1998), Nia and Lynne Zaichkowsky (2000), Rutter and Bryce (2008), and Bian and Moutinho (2009)
	Qualitative	Psychological and contextual antecedents.	Eisend and Schuchert-Güler (2006)
Consequences	Analytical Model	Counterfeiting on competition and welfare.	Grossman and Shapiro (1988)
	Field Data & Analytical Model	Counterfeiting can stimulate innovation and alter firms' strategy.	Qian (2008), Qian (2014), and Qian, Gong, and Chen (2015)
B. Luxury/Conspicuous/Status Goods Demand			
Who/Why Buy?	Field Data	Using Consumption data shows racial differences in the incentives for conspicuous consumption.	Charles, Hurst, and Roussanov (2009)
	Analytical Model	Status signaling and exclusivity drive luxury markups through prestige and social recognition motives.	Leibenstein (1950), Bagwell and Bernheim (1996), Amaldoss and Jain (2005a), and Kuksov and Xie (2012)
	Survey	Luxury products have signaling functions.	Scott, Mende, and Bolton (2013) and Wang and Griskevicius (2014)
Firm Strategy	Analytical Model	Social utility drives pricing and branding strategy in status markets.	Amaldoss and Jain (2005b) and Amaldoss and Jain (2015)
C. Piracy in Digital Industry			
Music Industry	Field Data	Sales displacement and welfare effects of piracy.	Rob and Waldfogel (2006), Hui and Png (2003), Smith and Telang (2009), Danaher et al. (2010), and Zhang (2018)
Software	Analytical Model or Field Data or Survey	The intentions and impact of piracy.	Gopal and Sanders (1998), Moores and Chang (2006), and Wang, Li, and Singh (2018)
Firm Strategy	Analytical Model	Firm decisions and pricing in response to piracy.	Sundararajan (2004), Chen and Png (2003), and Chellappa and Shivendu (2005)

Note: Table A.1 organizes related work into three strands: (A) counterfeit demand; (B) demand for luxury/conspicuous/status goods; and (C) digital piracy. For each strand, we list core research questions, method/data, key ideas, and representative studies.

Figure A.1: Brand Keyword Search Pattern On The Platform



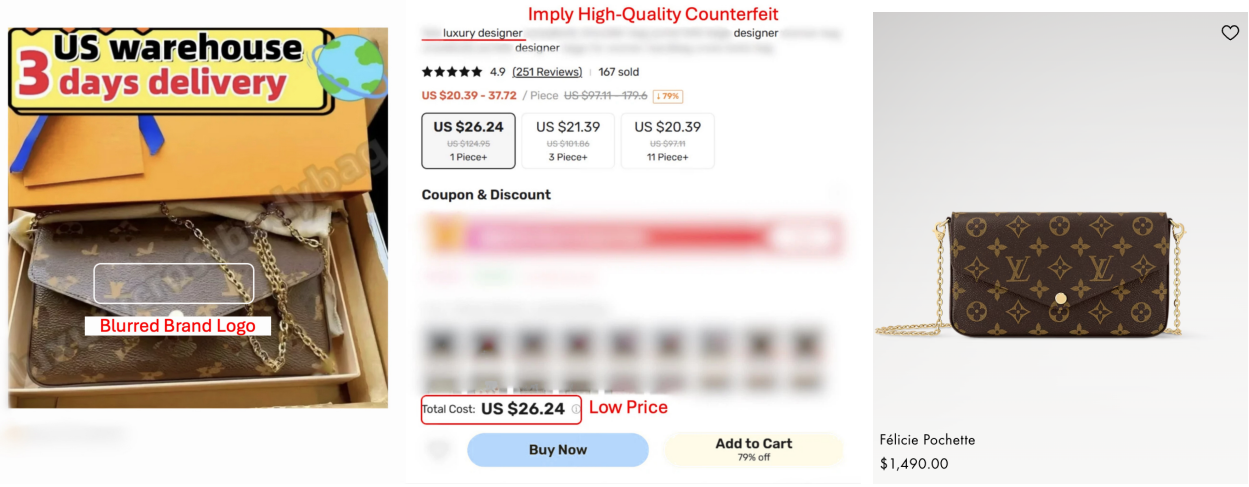
(a) Searching Correct Brand Name Returns No Result



(b) Searching Misspelled Brand Name Returns 279,769 Results

Note: Figure A.1 contrasts search outcomes for the correctly spelled versus misspelled brand name on the platform. The query "louis vuitton bag" (Figure A.1a) yielded 0 results, whereas "louis vuittonn bag" (Figure A.1b) returned 279,769 results. Searches performed on 2 October 2024.

Figure A.2: Counterfeit Product Page On The Platform vs. The Real Product



(a) Product Page On The Platform (b) Real LV Product Page

Note: Figure A.2 contrasts the platform's product page with the authentic one. In Figure A.2a, brand identifiers are obscured by a mosaic image; the code phrase "luxury designer"–a common euphemism for branded replicas–and assigns the quality grade "10A," shorthand for a high-grade counterfeit. Its price is only 1.7% of the authentic item's $1,490 price shown in Figure A.2b.

imitates the genuine product yet sells for only 1.7% of the authentic price. Many vendors add branded boxes, dust bags, and even spurious authentication cards. Quality varies, but some copies are reported to be almost indistinguishable from the originals.[2]

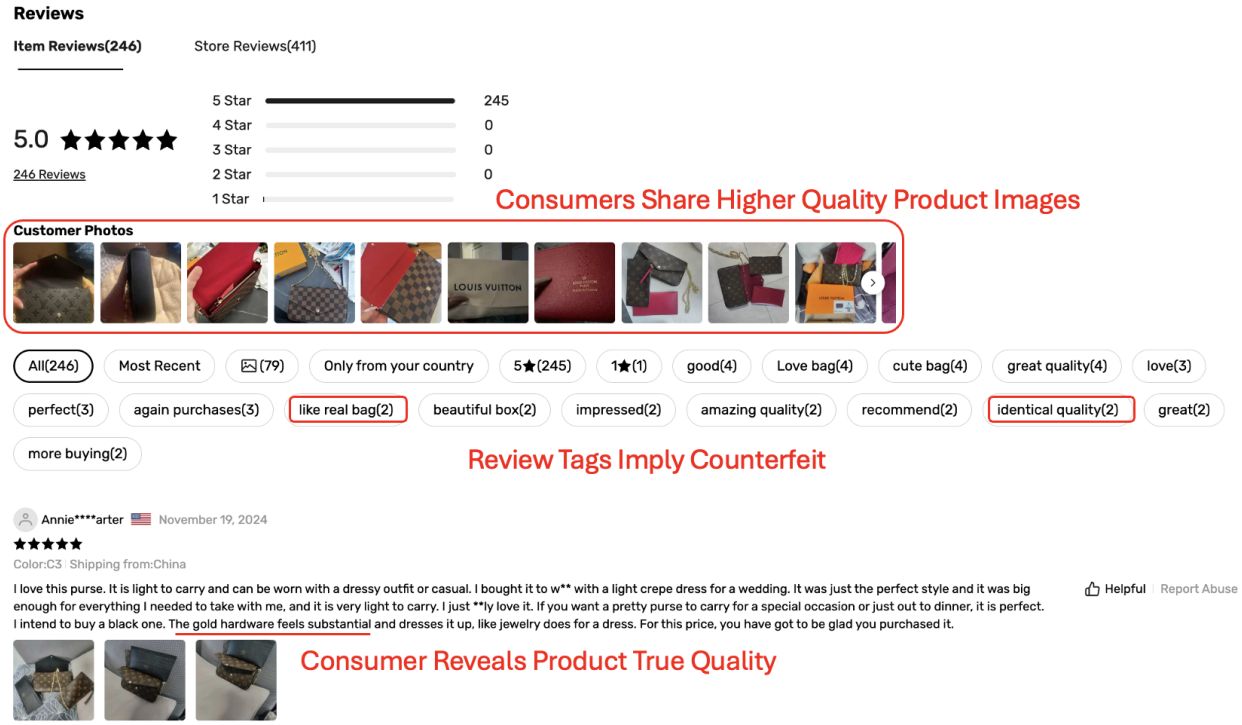
Demand side. Consumers on the platform are generally aware that they are buying counterfeits. First, prices signal inauthenticity. Items that copy well-known mass market brands sell for a small fraction of retail: about 29.6% for less conspicuous labels such as Nike and UGG, and about 2.2% for conspicuous labels such as Louis Vuitton and Gucci . Second, behavior confirms intent. More than two-thirds of orders come from repeat buyers, indicating sustained engagement rather than chance purchases. Third, user-generated content reinforces awareness. Across Reddit, TikTok, and YouTube, buyers post unboxing videos, reviews, and step-by-step guides, openly discussing how to source counterfeits on the platform.[3]

Buyers fill information gaps left by sellers, a phenomenon described by Mansfield and Mattern (2023) as "the new frontier for the sale of fakes." Sellers, keen to limit liability, omit trademarks and describe items as "unbranded," creating information asymmetry. Reviews counter this by showing what was delivered, naming the brand, and rating the quality. In Figure A.3, buyers upload photos of goods bearing the Louis Vuitton monogram and note that "the gold hardware feels substantial" and the bag is "exactly like the original." Such comments recognise the counterfeit nature of the product and judge it by its resemblance to the authentic version. Demand-side reviews thus help sustain the market's veil of secrecy.

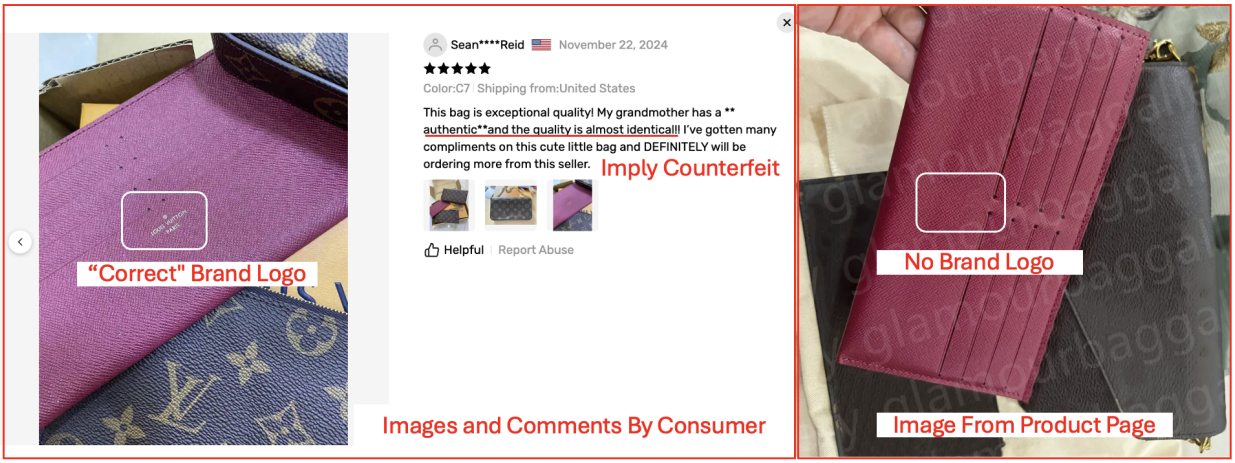
[2] A survey of its top sellers, presented in Appendix B.1, indicates that 90% sell counterfeit goods.

[3] Appendix B.2 conducts a survey on the platform's subreddit and finds that 88.1% of posts–virtually every product-related post–involve existing or desired counterfeit listings of established brands.

Figure A.3: Reviews Share "Better" Product Information



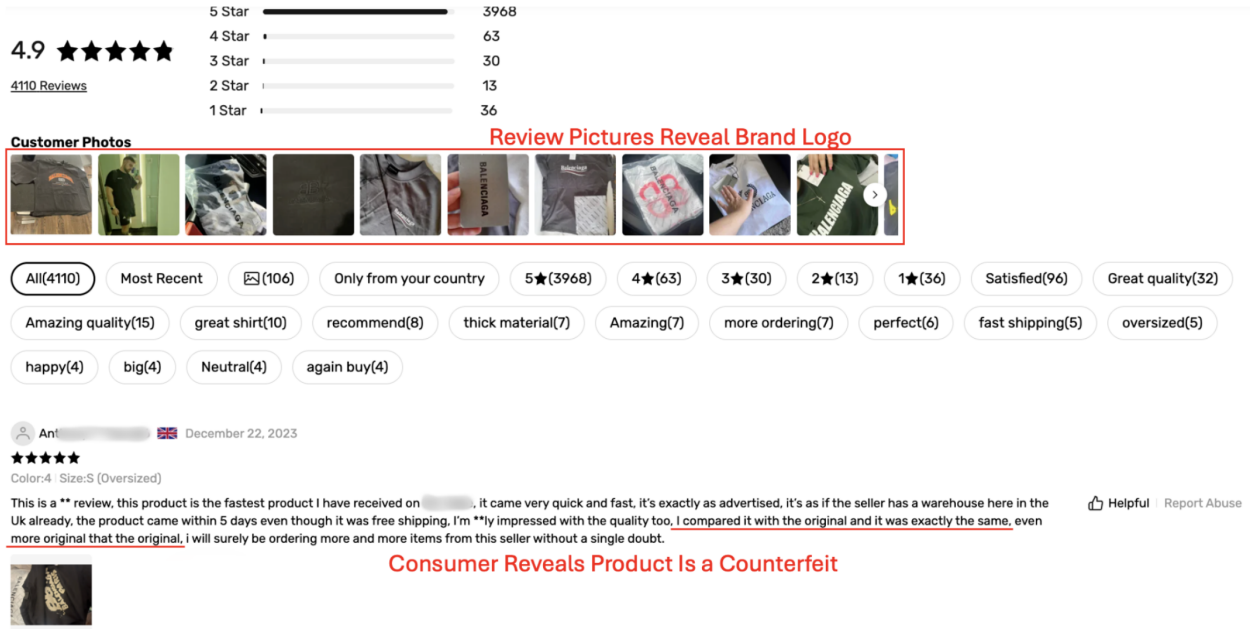
(a) Review Summary



(b) Review Image (By Buyer) vs. Product Page Image (By Seller)

Note: Figure A.3 shows product reviews of an item. In Figure A.3a, buyers can view product ratings, see real photos from previous customers, and read review tags such as "like real bag." In Figure A.3b, the middle section shows the focal product review, which states the product is "almost identical" to the authentic one, featuring a true product photo with the brand logo (left). The right side of Figure A.3b comes from the product page made by the seller, which appears lower in quality than the buyer's review suggests.

Figure A.4: Example of Survey Evidence From Consumer Review



Note: Figure A.4 displays a review whose buyer-uploaded photos show brand logos and whose text calls the item "exactly the same" as the authentic product; this evidence satisfies criterion (i) for classifying a store as selling counterfeits.

B.1 Survey Evidence on Selling Counterfeits

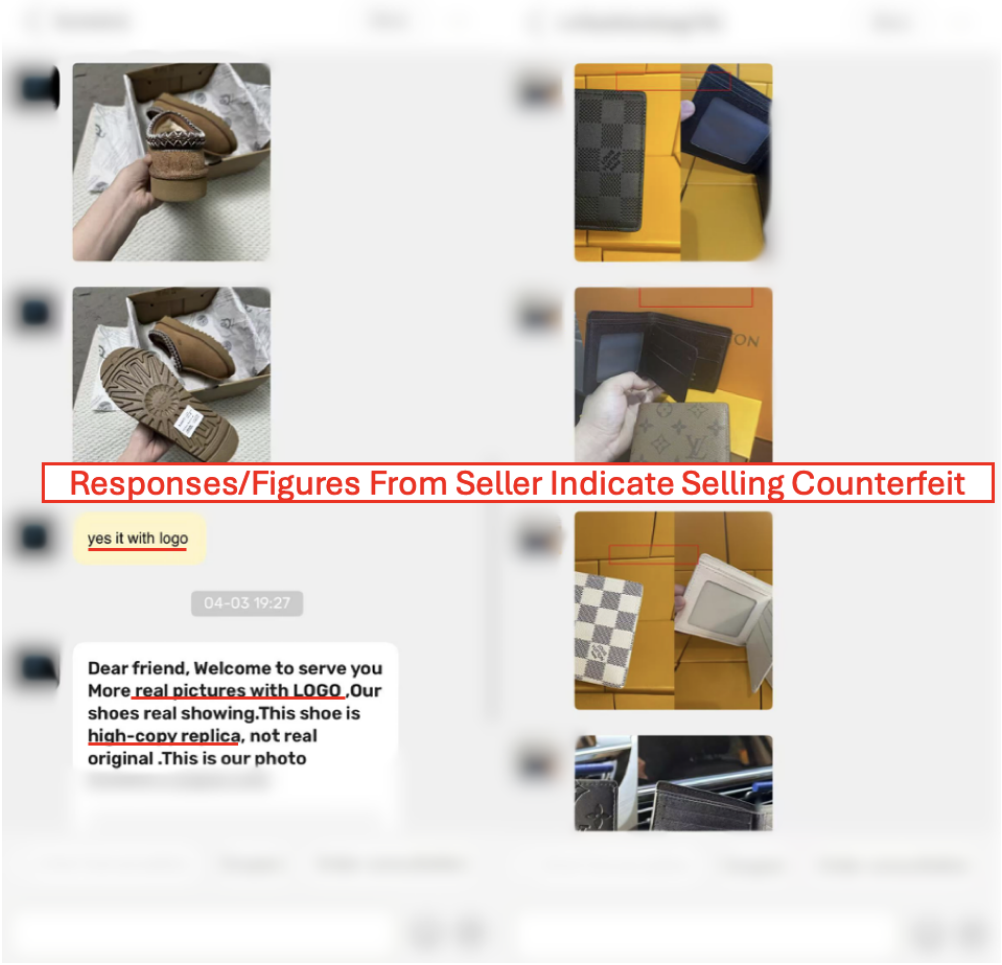
To verify the prevalence of counterfeits on the platform, we conduct a survey of top-selling stores using a combination of publicly available information and seller-provided responses.[4] We are careful not to classify unbranded products as counterfeits, focusing solely on items explicitly copying known brands. Formally, we classify a seller as offering counterfeits if at least one of the following conditions is met: (1) consumer-uploaded review photos display a known brand logo (see Figure A.4); (2) Reddit posts explicitly identify the seller as offering counterfeits (see Figure A.5); or (3) the seller directly provides photos showing brand logos upon request (see Figure A.6). We sequentially apply these criteria: if criterion (1) provides no conclusive evidence, we move to criterion (2); if uncertainty remains, we proceed to criterion (3). As shown in Table A.2, among the 120 surveyed stores, 108 are identified as selling counterfeits. The remaining stores sell electronic devices (e.g., USB-C chargers) or "do-it-yourself" (DIY) products.

[4]The survey is conducted exclusively for academic research.

Figure A.5: Example of Survey Evidence From Reddit

Note: Figure A.5 reproduces a thread from the platform's subreddit in which potential buyers cite specific seller names (redacted for anonymity) and call the goods as "1 : 1" replicas—virtually indistinguishable from the authentic items. Such open acknowledgement of counterfeiting satisfies classification criterion (ii) for flagging a store as a counterfeit seller.

Figure A.6: Example of Survey Evidence From Seller Reply



Note: Figure A.6 reproduces a seller's response to a request for more details. The seller supplies photos that display brand logos and explicitly writes that the item is a "high-copy replica, not real original," thereby satisfying classification criterion (iii) for identifying a counterfeit store.

Table A.2: Summary of Store Survey Results

Category	Number of Stores	Percentage (%)
Total Stores Surveyed	120	100.0
Stores Identified as Selling Counterfeits	108	90.0
– Brand Logo in Review Photos	84	70.0
– Explicitly Identified by Reddit Posts	16	13.3
– Sellers Providing Brand Logo Photos upon Request	8	6.7

Note: Table A.2 reports a survey of top-selling stores on the platform. A store is classified as counterfeit if any of the following are observed: (i) buyer reviews contain photos that clearly display brand logos; (ii) Reddit threads name the seller as offering counterfeit items; or (iii) when prompted, the seller supplies product images bearing brand logos.

B.2 Post Analysis on the Platform's Subreddit

We sampled 953 unfiltered posts from the platform's subreddit over a fixed time window to examine social media's role in mitigating information asymmetry in counterfeit markets. We predefined content categories and used ChatGPT `o4-mini` to classify each post. We then manually checked all classification results. The final distribution is presented in Table A.3. Overall, 88.1% of posts involve existing or desired counterfeit listings of established brands. Nearly all posts that mention a specific product pertain to counterfeits rather than genuine items.

Table A.3: Post Analysis From The Platform's Subreddit

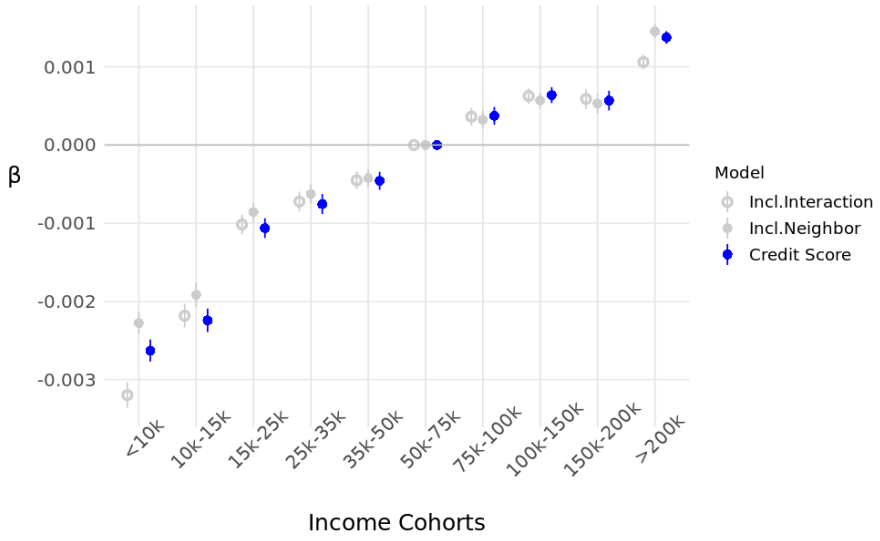
Post type	Count	Percentage	Example / comment
Counterfeit–related			
Ask for desired item	566	59.4%	"Looking for *[brand name] [size]* "
Ask for best seller	45	4.7%	"Best seller this product? [photo of *[brand name]* "
Evaluate item condition	138	14.5%	"*[brand name]*: First time buyer, what do you guys think?"
Review a seller / item	91	9.5%	"Review: *[brand name] [size]* from *[store name]*"
Subtotal	840	88.1%	
Non-counterfeit			
Other	20	2.1%	[Site issues, unrelated help]
Logistics daily thread	59	6.2%	[Shipping / logistics thread]
Random tip of the day	29	3.0%	[The platform's parcel-tracking service is old. For better, try this.]
Coupons and giveaway	5	0.5%	[Coupons and giveaway]
Subtotal	113	11.9%	
Total	**953**	**100.0%**	

Note: Table A.3 classifies 953 randomly sampled subreddit posts. Bracketed text is supplied by the authors for illustration.

C Credit Score As A Benchmark

To benchmark the size of our estimates—and given possible attenuation from measurement error in ZIP-code income—we re-estimate Equation 1 using ZIP-code credit scores (an outcome tightly linked to income) as the dependent variable. Counterfeit demand varies by about 4% across income

Figure A.7: Income and Credit Score



Note: Figure A.7 summarizes the credit-score–income gradient; gray circles denote alternative specifications that control for spillovers, estimated with the same specifications as Figure 1a but using credit score as the outcome. To ensure comparability, we apply the same outcome transformation so the estimates admit a percentage interpretation. The $50,000–$75,000 cohort is the reference group. Whiskers indicate 95% confidence intervals.

cohorts, whereas credit scores vary by roughly 0.2% (Figure A.7). The much smaller dispersion in credit scores indicates that the income gradient in counterfeit demand is economically meaningful.

D Interpretations and Robustness

We conduct three sets of additional analyses to assess the robustness of our interpretation.

D.1 Spillovers vs. Own-Cohort Effects

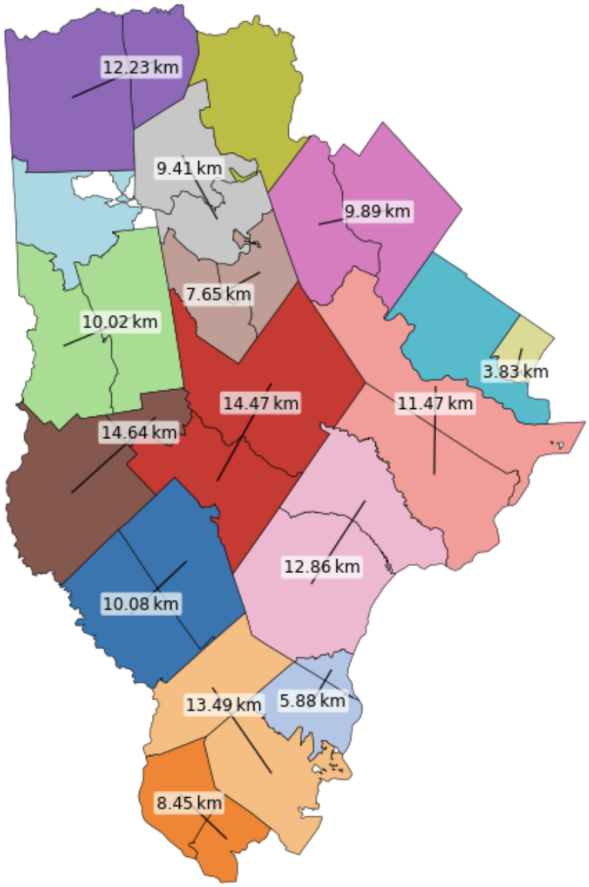
Our interpretation of the U-shape assumes that a cohort's counterfeit demand is driven primarily by its *own* income share, rather than by cross-cohort spillovers (Charles, Hurst, and Roussanov 2009). We assess this in two ways. First, we augment Equation 1 with an interaction between the ZIP's high- and low-income shares, allowing each tail's demand to vary with the presence of the other. Specifically

$$\begin{aligned}\text{Counterfeit\_Demand}_i = \beta_0 + \sum_{j \neq j_M} \beta_j \cdot \text{Income\_Cohorts}_{ij} \\ + \gamma \cdot \text{Income\_Less\_10k}_i \times \text{Income\_More\_than\_200k}_i + \epsilon_i.\end{aligned} \tag{A.1}$$

The resulting $\hat{\beta}_j$'s are shown as gray hollow circles in Figure 1a.

Second, we control for the full income composition of the nearest ZIP code, allowing neighboring

Figure A.8: Neighboring ZIP code: An Example



Note: Figure A.8 illustrates the nearest-neighbour matching for ZIP codes in York County, ME. ZIP codes shaded in the same colour form a matched pair; numbers on the connecting lines give the centroid-to-centroid distance in kilometres. ZIP codes without a same-county match (e.g., Newfield, the light-blue area in the upper left) are paired with a neighbouring ZIP code outside York County.

income mixes to affect local demand. Specifically

$$\text{Counterfeit\_Demand}_i = \beta_0 + \sum_{j \neq j_M} \beta_j \cdot \text{Income\_Cohorts}_{ij} + \sum_{j \neq j_M} \delta_j \cdot \text{Income\_Cohorts}_{\mathcal{N}(i),j} + \epsilon_i. \quad \text{(A.2)}$$

$\text{Income\_Cohorts}_{\mathcal{N}(i),j}$ denotes the share of households in income cohort j in the ZIP code $\mathcal{N}(i)$, the nearest geographic neighbor of ZIP i. Across the full sample the mean distance between matched neighboring ZIP codes is 10.86 km (see Figure A.8 for an illustration). The corresponding $\hat{\beta}_j$'s are shown as gray solid circles in Figure 1a.

In both specifications, the U-shape remains, suggesting that cross-income-cohort spillovers are not the primary driver.

D.2 Contextual Heterogeneity

Our main estimates use ZIP-code aggregates to infer underlying individual behavior. It rests on the assumption that preference profiles, β_j, do not vary systematically across places in a way that could

Table A.4: ZIP-Level Demographics

	N	mean	std	min	25%	50%	75%	max
Median_Income	24,721	75,098	31,465	9,145	54,741	68,348	87,618	250,000
Gini_Index	24,721	0.425	0.062	0.08	0.388	0.423	0.462	0.737
Median_Age	24,721	42.15	7.50	11.9	37.3	41.4	46.3	82.9
Sex_Ratio	24,721	102.53	28.76	21.0	92.5	99.2	107.6	2398.10

Note: Table A.4 reports descriptive statistics for all U.S. ZIP codes with at least one observed order. Sex_Ratio denotes the number of males per 100 females, where values above 100 indicate male-majority areas.

mechanically generate the observed pattern. If they did, ZIP-level estimates might fail to reflect individual-level associations. We gauge sensitivity by re-estimating Equation 1 in split samples. For each contextual variable—median income, income dispersion (Gini), median age, and the sex ratio—we partition ZIP codes at the median and re-estimate in the high and low subsamples. Table A.4 contains a summary for the four contextual variables over all ZIP codes in our sample. If the pattern reflects individual preferences rather than neighborhood composition, it should persist within each stratum. As shown in Figure A.9, the U-shape appears across all subgroups (with only modest variation in magnitude), indicating that the result is not driven by any single local context.

D.3 Buyer Types: Extensive vs. Intensive Margin

We examine whether the U-shaped pattern is driven by the extensive or intensive margin. Specifically, we ask: (i) does it primarily reflect one-off "novelty" purchases?[5] and (ii) could higher activity among high-income consumers simply reflect greater purchasing power—more purchases per buyer rather than a greater propensity to enter?

To assess these mechanisms, we classify buyers by their purchase histories: *one-time* buyers place a single order, and *repeat* buyers place two or more. We then compute, by ZIP code, the number of unique buyers of each type per household. Figure A.10a shows that the U-shape holds for both one-time and repeat buyers, indicating that the income–demand relationship is not driven solely by entry or by repeat purchasing.

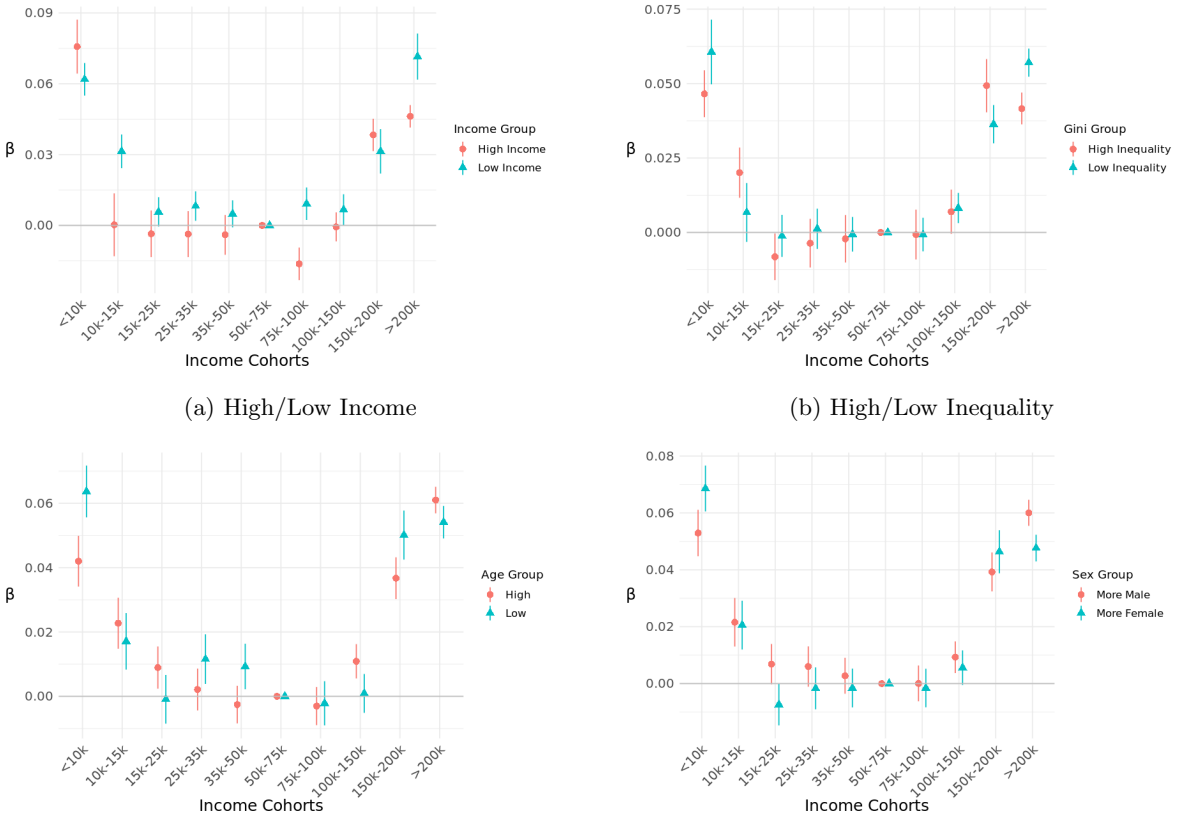
Among repeat buyers, we further distinguish *same-brand* repeaters (at least two orders from the same brand) from *new-brand* repeaters (repeat orders span different brands). Figure A.10b shows a U-shaped income gradient for both groups, indicating that the pattern persists within repeat behavior—both within-brand retention and cross-brand exploration.

E Popularity Measure at Product Series Level

To assess whether the "treasure-hunt" mechanism is sensitive to the unit of popularity aggregation, we replicate the popularity analysis at the product-series level. Specifically, we aggregate sales across all listings within a series, which mitigates the concern that listing-level popularity may partly reflect seller effects. Based on the sales cutoffs in Figure A.11b, we classify series into four

[5]Survey evidence in Appendix B suggests inadvertent counterfeit buying is unlikely.

Figure A.9: Counterfeit Demand By Contextual Factor



(a) High/Low Income

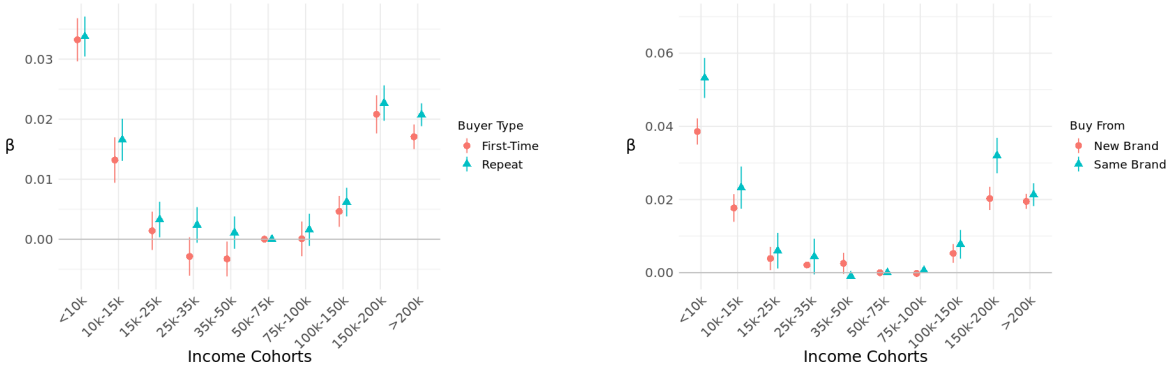
(b) High/Low Inequality

(c) High/Low Age

(d) More Male/Female

Note: Figure A.9 presents the re-estimation of Equation 1 in split samples to assess contextual heterogeneity. ZIP codes are divided at the median of each contextual variable, and the model is estimated separately for the high and low groups. Specifically, Figure A.9a, Figure A.9b, Figure A.9c, and Figure A.9d respectively show the results by median income, income inequality (Gini), median age, and sex composition. For the sex-based split, ZIP codes are divided according to whether there are more males or more females (sex ratio above or below 100). The U-shaped pattern persists in all splits. Middle-income households ($50,000–75,000) serve as the reference group for each group. Whiskers denote 95% confidence intervals.

Figure A.10: Income and Counterfeit Demand: By Buyer Behavioral Type



(a) By Buyer Experience

(b) By Buyer-Brand Prior Interaction

Note: Figure A.10 reports income-cohort effects estimated via Equation 1, using as the outcome the number of unique buyers per N households (inverse-hyperbolic-sine transformed). Figure A.10a contrasts first-time buyers (red circles) with repeat buyers (green triangles). Figure A.10b decomposes repeat buyers into cross-brand repeaters (red circles) and same-brand repeaters (green circles). Markers denote demand intensity; whiskers are 95% confidence intervals. The \$50,000–\$75,000 cohort is the reference group.

popularity groups: very niche, niche, popular, and very popular. Figure A.11a shows that the U-shaped income pattern persists across popularity tiers under this alternative measure, consistent with the listing-level results in the main analysis.

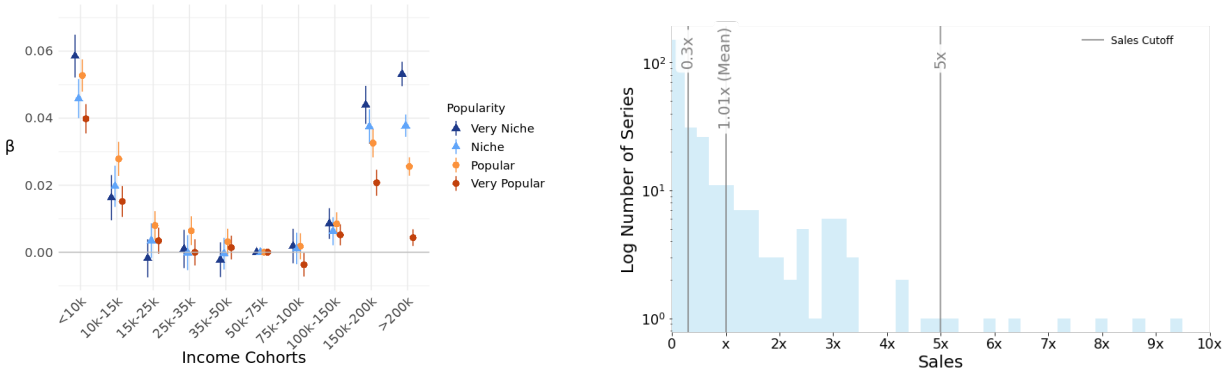
F Brand Segment and Product Series Classification

Brand segment. Table A.5 classifies brands by their brand-level average authentic retail price across product series in our dataset. We analyze bags and shoes separately to account for category differences in Section 3.2.2. For bags, we distinguish three tiers. Accessible Luxury brands have average authentic retail prices between \$700 and \$1,500 and include Coach, Tory Burch, Telfar, and Marc Jacobs. Premium Luxury brands, priced between \$2,000 and \$4,000, include Gucci, Burberry, Dior, Fendi, Saint Laurent, Loewe, and Prada. Ultra-Luxury brands, priced above \$6,000, are represented by Hermès and Chanel. For shoes, we separate mass-market shoes with authentic retail prices below \$200, such as Nike, New Balance, UGG, and Jordan/Yeezy lines, from luxury shoes priced between \$300 and \$2,500, including Golden Goose, Alexander McQueen, Gucci (shoes), and Louis Vuitton (shoes).

Product series. Table A.6 presents a brand-series–level classification for four representative brands (Hermès, Chanel, Louis Vuitton, and Nike), grouping series into three types based on their position in the brand's product-line hierarchy.

Classic series are long-running signature designs that define a brand's identity and occupy a central position in its heritage, such as the Hermès Birkin and Kelly, the Chanel Classic Flap and 2.55, the Louis Vuitton Speedy and Neverfull, and Nike's Air Force 1 and Air Max. These products exhibit persistent demand, strong resale markets, and high symbolic salience.

Figure A.11: Counterfeit Demand by Popularity: Product-Series Level



(a) By Series Popularity

(b) Sales Distribution

Note: Figure A.11a plots counterfeit demand across income cohorts by series popularity, estimated using Equation 1. The $50,000–$75,000 income cohort is the reference group. Whiskers denote 95% confidence intervals. Series popularity is measured by aggregating sales across all listings within a series (e.g., LV Neverfull). Figure A.11b shows the distribution of series-level sales (logarithmic y-axis); sales are in normalized units (e.g., x, $2x$) for confidentiality; vertical gray lines mark the threshold cutoffs.

Table A.5: Brand Segmentation

Category	Segment	Authentic Price	Brands	Ratio	Price
Bags	Accessible Luxury	$700–$1,500	Coach, Telfar, Marc Jacobs, Tory Burch	8.35%	$32.59
	Premium Luxury	$2,000–$4,000	Gucci, Burberry, Dior, Fendi, Saint Laurent, Loewe, Prada	1.77%	$45.94
	Ultra-Luxury	$6,000+	Hermès, Chanel	0.55%	$54.24
Shoes	Mass-Market	< $200	UGG, Nike, New Balance, Air Jordan, Yeezy	35.05%	$48.98
	Luxury	$300–$2,500	Golden Goose, Alexander McQueen, Gucci (Shoes), LV (Shoes)	10.70%	$65.33

Note: Table A.5 shows brand segments information. Authentic prices estimated from official brand sources. Ratio denotes the mean counterfeit-to-authentic price ratio, and Price reports the average counterfeit transaction price. Price dispersion among counterfeits is markedly smaller than among authentic goods.

Fashion series consist of newer or trend-driven lines whose prominence is shaped by seasonal appeal, design innovation, or collaborations, including the Chanel 19 and 22 bags, Louis Vuitton's Twist and Coussin, and Nike's VaporWaffle collaboration line. Their demand and symbolic relevance tend to vary more over time.

Past-season series include legacy designs or short-lived models that no longer occupy a core position in the current lineup, such as the Hermès Herbag, the Chanel Boy Bag, the Louis Vuitton Petite Malle, and the Nike Blazer. These products generally have lower symbolic centrality and more limited resale potential.

Table A.6: Brand Series Classification

Brand	Type	Series (with Launch Years)	Authentic Price	Description
Hermès	Classic	Kelly (1930s), Constance (1959), Birkin (1984)	\$10,000+	Core heritage icons that define Hermès' identity; prices show sustained long-term appreciation.
	Fashion	Lindy (2007), Garden Party, Picotin (2002), Evelyne (1978)	\$3,000–\$9,000	Accessible within the brand's range
	Past Season	Herbag (1998)	\$2,500–\$3,500	Entry-level canvas–leather hybrid; modest pricing and limited resale potential.
Chanel	Classic	2.55 Reissue (1955), Classic Flap (1983)	\$10,000–\$12,000	Foundational designs that anchor Chanel's heritage; prices have risen nearly 30% since 2022.
	Fashion	19 Bag (2019), 22 Bag (2022)	\$6,000–\$7,000	Contemporary releases under modern creative direction.
	Past Season	Boy Bag (2011)	\$5,000–\$6,000	Early hit; now discontinued.
Louis Vuitton	Classic	Speedy (1930), Alma (1934), Pochette, Neverfull (2007), NeoNoé (2017)	\$1,500–\$3,000	Long-standing bestsellers maintaining consistent demand and resale value.
	Fashion	Dauphine (2019), Onthego, Coussin (2021), Twist (2015)	\$3,000–\$5,500	Fashion-forward collections reflecting creative renewal.
	Past Season	Capucines (2013), Petite Malle (2014), Pont 9 (2020)	\$4,000–\$7,000	Limited or collector-focused lines.
Nike	Classic	Air Force 1 (1982), Air Max (1987), Dunk (1985)	\$110–\$180	Core athletic models defining Nike's 1980s heritage; affordable and culturally enduring.
	Fashion	VaporWaffle (Sacai, 2020)	\$200–\$250	High-fashion collaboration blending performance and couture.
	Past Season	Nike Blazer (1972)	\$90–\$120	Early basketball model.

Note: Table A.6 classifies each brand's series into three types. The Series column lists representative models within each category along with their launch years. Authentic prices are estimated from official brand sources, and additional classification rationales are provided in the Description column.

G Co-Purchase Network Technical Details

Using anonymized buyer IDs, we link each buyer to her purchase history and construct a buyer–brand incidence matrix. We then form a weighted brand network, where edge weights reflect buyer overlap (share of buyers purchasing both brands). Communities are identified using the Infomap algorithm (with multiple runs for stability). For readability, we retain each brand's strongest ties (Top-K

pruning) and apply a force-directed layout so that brands with stronger co-purchase links appear closer. Node size reflects centrality (overall co-purchase strength), edge thickness indicates tie intensity, and node color denotes Infomap communities.

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